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Tailoring AI Chatbots to User Motivation:
Performance-Approach Versus Performance-Avoidance Effects on Continuance Intention

Chang Heon Lee
https://orcid.org/0000-0002-3906-8462
California State University, Fresno, USA

Stephen Choi
https://orcid.org/0000-0003-0878-0649
California State University, Fresno, USA

Ojoung Kwon
https://orcid.org/0009-0005-2496-7261
California State University, Fresno, USA
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ABSTRACT

As AI-powered chatbots become increasingly integrated into organizations, understanding the motivational factors that influence their continued use is essential for maximizing return on investment. While previous research has emphasized functional attributes, less attention has been paid to individual motivational orientations. This study integrates goal orientation theory into chatbot continuance research to explain how motivational dispositions shape evaluative pathways toward sustained use. Performance-approach orientation enhances perceptions of novelty value and hedonic attitude and maintains a direct positive link to continuance intention. In contrast, performance-avoidance orientation does not directly affect continuance; instead, it indirectly influences sustained use by strengthening utilitarian cognitive attitudes and performance expectancy. These distinct pathways demonstrate the pivotal role of goal orientation as an antecedent, driving either affective or utilitarian mechanisms in sustained chatbot use.

KEYWORDS

AI Chatbot, Goal Orientation, Continuance Intention, Performance-Approach Goal, Performance-Avoidance Goal, Goal-Directed Behavior

INTRODUCTION

Artificial intelligence (AI) technologies are rapidly transitioning from research labs to all facets of professional life, driving changes in how employees adopt and utilize intelligent tools in the workplace (Nguyen et al., 2021; Wu et al., 2024). Also known as intelligent virtual assistants, chatbots are text-based or voice-driven conversational agent systems that support tasks ranging from customer service to workflow management (Adam et al., 2021; Pillai & Sivathanu, 2020; Polyportis & Pahos, 2025). AI chatbots for businesses have gained substantial global attention for their ability to automate tasks and provide innovative insights for complex jobs. These intelligent chatbots are

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becoming integral to business operations and everyday workflows, offering new possibilities for efficiency and creativity in work (Gkinko & Elbanna, 2023; Haleem et al., 2022; Labadze et al., 2023).

With the rise in chatbot usage, academic research has also increased across various aspects, ranging from adoption to design artifacts (Gupta et al., 2024; Li et al., 2025; Xing et al., 2023). Prior studies have primarily focused on factors driving the initial adoption of chatbots, drawing on technology adoption models. For example, researchers have applied the technology acceptance model and the unified theory of acceptance and use of technology (UTAUT) to identify key determinants of adoption, such as perceived usefulness, ease of use, trust, and anthropomorphism. Other work, utilizing frameworks such as uses and gratifications theory, has examined whether users seek chatbots for utilitarian purposes (e.g., task assistance), hedonic purposes (e.g., enjoyment or fun), social interaction, or symbolic value. Through these lenses, studies have found that both utilitarian and hedonic benefits can drive individuals' intentions to adopt chatbots. Common predictors of chatbot adoption include perceived ease of use, perceived usefulness, enjoyment, trust, and its human-like qualities.

Despite extensive research examining AI chatbot adoption through established frameworks such as the technology acceptance model, UTAUT, and uses and gratifications theory (Gupta et al., 2024; Ma & Huo, 2023; Rahi et al., 2019), significant limitations persist in current understanding. First, existing studies predominantly concentrate on the pre-adoption and initial acceptance phases, with insufficient attention to post-adoption continuance behaviors that ultimately determine system success (Balakrishnan et al., 2022; Ma & Huo, 2023). The problem is that, while many adoption studies claim comprehensive coverage of technology acceptance, we find considerable work that focuses on initial usage without addressing sustained engagement patterns. Second, current research often treats users as a homogeneous population, overlooking individual differences in motivational orientations that may fundamentally shape technology engagement patterns (Choudhury & Shamszare, 2023; Kuberkar & Singhal, 2020). The impact of this oversight is significant, as recognizing motivational heterogeneity is crucial from an organizational perspective. It directly affects engagement, performance, and satisfaction, making it a key consideration. Third, the extant literature lacks theoretical grounding in psychological motivational constructs that could explain why individuals with different goal orientations exhibit varying patterns of sustained technology use (Pillai & Sivathanu, 2020).

Recent work has begun to address continuance by applying post-adoption perspectives—especially expectation-confirmation models—showing that experiential and gratification factors influence intentions to continue using AI chatbots (Bhatnagr & Rajesh, 2024; Dhiman & Jamwal, 2023; Sundjaja et al., 2025). Likewise, in financial services, quality attributes such as accuracy and interactivity have been linked to post-adoption continuance (Dhiman & Jamwal, 2023). These studies highlight that user experience factors are pivotal for sustained use. However, most established models of information systems (IS) continuance assume that post-adoption outcomes are shaped primarily by system attributes or interaction quality. In other words, prior research tends to treat experiential factors as arising from what the system does. While this approach has yielded important insights, it overlooks the point that users interpret their experiences through their motivational filters. What one user perceives as enjoyable or novel, another may view as merely efficient. This raises an important but underexplored question: How do users' motivational dispositions affect their perceptions and evaluations of AI chatbot experiences in the post-adoption stage? Addressing this question can explain variability in continuance intentions that system attributes alone cannot.

This study examines chatbot continuance through the lens of performance goal orientation. Performance goal orientation encompasses achievement-oriented behavioral patterns in which individuals focus on demonstrating competence relative to others; two distinct orientations—performance-approach (PAP) and performance-avoidance (PAV)—tend to engender different cognitive evaluations and behavioral responses (Dweck, 1986; Elliot & Church, 1997; Elliot & Thrash, 2001; VandeWalle et al., 2001). The underlying psycho-social dynamics can facilitate or impede user engagement as individuals navigate technological interactions and strive for optimal utilization (Alhadabi & Karpinski, 2020). The use of an AI chatbot for work tasks is an achievement-related activity: users may employ the chatbot either to excel (e.g., generate creative ideas, solve complex problems) or to avoid failure (e.g., double-check answers, minimize errors). Applying goal orientation to chatbot use, PAP-oriented users, driven to achieve and explore, likely see an AI chatbot as a performance enhancer or a proactive tool. Conversely, PAV-oriented users are likely to approach it with a preventative focus on error avoidance. Their primary motive is to avoid failure or negative outcomes. Thus, they will be more concerned with the chatbot's reliability and efficiency—the utilitarian benefits that help them avoid mistakes.

Prior technology adoption research has only sporadically examined achievement motivations. An early study by Mun and Hwang (2003) found that individuals with strong learning goals showed a greater intention to use web-based systems. More recently, Tojib et al. (2022) demonstrated that performance-based goal orientations (approach vs. avoidance) influenced customers' openness to adopting service robots. These studies suggest that users' goal orientations influence the continued use of new technologies. To our knowledge, no prior work has integrated goal orientation to explain the continuance of AI-powered chatbots in the workplace.

Given these gaps, this study aims to examine how performance goal orientations influence users' post-adoption evaluations and continued use of AI chatbots. Drawing on goal orientation theory, we analyze how users with different motivational profiles evaluate chatbot interactions, the continuance intentions their orientations generate, and the roles of hedonic and cognitive responses during use. We expect PAP to strengthen continuance both directly and indirectly by increasing perceived novelty and hedonic attitudes. In contrast, PAV supports continuance through more utilitarian evaluations, including performance expectancy and related cognitive assessments. These parallel pathways highlight distinct drivers of sustained engagement and provide guidance for designing AI chatbots and engagement strategies that align with users' motivational differences.

Building on these theoretical predictions, we develop a research model grounded in performance goal orientation theory and the IS continuance paradigm. We then empirically test this model with survey data from experienced chatbot users in workplace settings. Our analysis employs partial least squares structural equation modeling to examine the relationships between goal orientations, intermediate perceptual factors (attitudes, expectancy, and novelty), and continuance intention. The results yield new insights into the motivational pathways that lead to sustained use of chatbots.

This study makes several contributions to research and practice. Theoretically, it introduces performance goal orientation as an important individual difference in the context of AI chatbot continuance, thereby bridging the gap between motivational psychology and IS research. We clarify how performance goal orientations differentially influence both hedonic evaluations and utilitarian evaluations of chatbots, which in turn drive continued use. The findings enrich our understanding of postadoption behavior by highlighting that "one size fits all" design or engagement strategies may be suboptimal—motivational segmentation is key. In practice, our work offers actionable guidance for organizations deploying AI chatbots: By aligning chatbot features and user support with the dominant goal orientations of their user base, they can enhance their long-term engagement. Ultimately, this research aims to support the sustained utilization of AI chatbots, ensuring these technologies provide lasting value rather than being abandoned after initial adoption.

LITERATURE REVIEW

Chatbot Continuance and Post-Adoption Behavior

Research has identified factors that influence individuals' attitudes and behaviors toward chatbots (Ma & Huo, 2023). Previous studies have applied theoretical frameworks, such as the technology acceptance model, the UTAUT, and uses and gratifications theory, to understand the motivations behind chatbot usage (R. or S. Gupta et al., 2024; Ma & Huo, 2023; Rahi et al., 2019). These frameworks suggest that chatbots serve various purposes: utilitarian, hedonic, symbolic, and social (Balakrishnan et al., 2022; Chen et al., 2022; Ma & Huo, 2023; Rahi et al., 2019). According to the existing literature, the predictors of chatbot adoption intention include perceived ease of use, perceived usefulness, perceived trust, perceived intelligence, and anthropomorphism (Balakrishnan et al., 2022; Gupta et al., 2024; Ma and Huo, 2023; Polyportis & Pahos, 2025).

Despite the extensive literature on the initial adoption of AI chatbots (Camilleri, 2024; Choudhury & Shamszare, 2023; Kuberkar & Singhal, 2020; Pillai et al., 2024; Zhou & Ma, 2025), a significant gap remains in understanding what happens after users have adopted these chatbots. Recent work has begun to address this by applying post-adoption perspectives, showing that experiential and gratification factors influence the continued use of AI chatbots (Bhatnagr & Rajesh, 2024; Dhiman & Jamwal,2023; Sundjaja et al., 2025). Likewise, in the financial services sector, quality attributes such as accuracy and interactivity have been linked to the post-adoption continuance of chatbots (Dhiman & Jamwal, 2023). These studies highlight that user experience factors are pivotal for sustained use. However, limited research has examined how individual user differences, particularly motivational dispositions, shape post-adoption perceptions and behaviors.

Performance Goal Orientation

Motivation research has identified two independent classes of goal orientations: the desire to achieve success and the desire to avoid failure (Ames & Archer, 1988; Downes et al., 2021; McClelland, 1961). Performance goal orientation has emerged as a central concept in educational and organizational psychology, describing individuals' tendencies to demonstrate competence and attain favorable judgments (Ames & Archer, 1988; VandeWalle et al., 2001). Goal orientation theory posits that individuals have goal orientation preferences in achievement situations: some focus on demonstrating success and competence, while others focus on avoiding failure or negative judgments (Dweck, 1986; Elliot & Thrash, 2001). In its contemporary form, goal orientation is typically divided into two categories: PAP, defined as the desire to achieve and outperform others, and PAV, defined as the desire to avoid failure and avoid appearing incompetent. These orientations represent distinct motivational mindsets that shape how individuals interpret challenges, set goals, and regulate their behavior (Dweck, 1986; Elliot & Church, 1997). The PAP-oriented individual is driven by the pursuit of achievement, whereas the PAV-oriented one is motivated by anxiety about mistakes and the desire to prevent adverse outcomes. Such motivational orientations influence learning strategies, task engagement, and receptivity to new tools across various contexts (Ames & Archer, 1988; VandeWalle et al., 2001).

Decades of research have demonstrated that PAP and PAV orientations result in distinct behavioral patterns (Alhadabi & Karpinski, 2020; Elliot & Harackiewicz, 1996; Lee & Chiravuri, 2019; Liu et al., 2021). PAP-oriented individuals exhibit more proactive and exploratory behaviors—they welcome challenging tasks and seek out opportunities to showcase skills (Elliot & Harackiewicz, 1996; Porath & Bateman, 2006). This orientation is known to be linked to higher levels of intrinsic motivation and creativity, as PAP-oriented individuals enjoy the process of excelling and frequently find innovative ways to achieve their goals. Conversely, PAV-oriented individuals tend to be more cautious and risk-averse (Elliot & Thrash, 2001). Individuals driven by avoidance tend to focus on preventing errors. In organizational psychology, a PAV orientation has been associated with defensive coping mechanisms aimed at preventing poor performance (Porath & Bateman, 2006).

Mun and Hwang (2003) found that goal orientation affected the use of web-based systems, highlighting the roles of perceived enjoyment and self-efficacy. More recently, researchers have begun to consider achievement motivations in the adoption of AI-driven systems; for example, one study suggested that employees with higher achievement striving were more likely to embrace enterprise AI tools for performance benefits (Cheng & Jiang, 2020). The findings suggest that motivation can affect technology acceptance. However, the dichotomy of PAP versus PAV has not, to our knowledge, been examined in relation to technology continuance. We expect this distinction to be highly relevant: Using an AI chatbot to assist with work or personal tasks is an achievement-related behavior, and users' predominant orientation (approach vs. avoidance) could influence not only whether they continue to use the chatbot but also how they experience it and what they value in it.

Relationship Between Goal Orientation and Motivational Usage of AI Chatbots

This study explores how goal orientations influence performance expectations, task values, and intention to continue using AI chatbot systems. Grounded in goal orientation theory, this study explicitly examines whether PAP goals shape users' behavioral intentions regarding chatbot continuance.

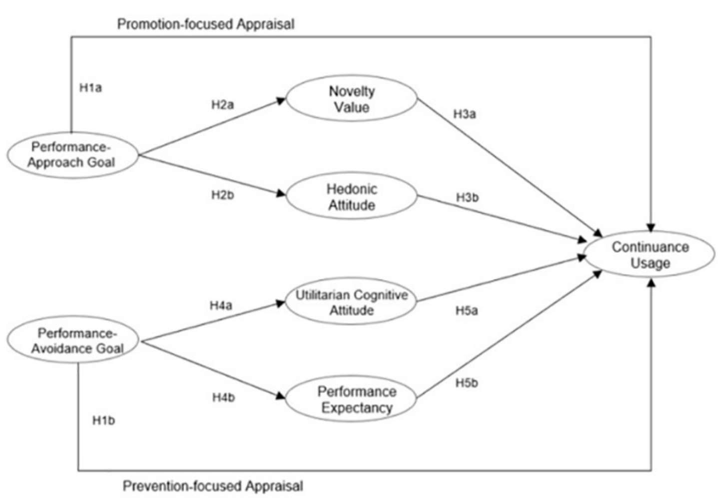
PAP-oriented users perceive AI chatbots as valuable tools that facilitate achieving their goals. They may view chatbots as innovative and creative resources that generate useful ideas for their tasks, while also experiencing them as enjoyable and engaging to use (Gupta et al., 2024). This hedonic attitude is partly attributed to the chatbots' innovative features and ability to produce novel, personalized outputs that support their performance goals (Cheng & Jiang, 2020). Consequently, their motivation to engage with chatbots is driven not only by a desire for enhanced performance recognition but also by the intrinsic enjoyment derived from the interaction rather than a sole emphasis on improving efficiency or effectiveness.

In contrast, PAV-oriented users tend to adopt a cautious and risk-averse approach, aiming to minimize the likelihood of failure in goal pursuit. This orientation aligns closely with the preventive use of AI chatbots, where the primary focus is on avoiding errors or undesirable outcomes (Alhadabi & Karpinski, 2020). Accordingly, PAV-oriented users are more likely to emphasize the utilitarian functions of AI chatbots—such as accuracy, reliability, and task support—while placing comparatively less value on hedonic or exploratory aspects of interaction, as observed among those with a high PAP orientation (Cheng & Jiang, 2020).

PAV-oriented users prioritize the chatbot's capability to minimize errors in task completion. They favor chatbots that provide clear instructions, anticipate potential mistakes, and offer corrective feedback to support accuracy at work. These users value reliability and risk mitigation, seeking features in generative AI chatbots that help prevent errors, ensure safety, and uphold task-relevant standards (Pillai & Sivathanu, 2020).

Figure 1 shows the proposed research model.

Figure 1. Proposed Research Model



HYPOTHESIS DEVELOPMENT

Performance Goal Orientation and Continuance Intention

Researchers have found that the goals individuals set for themselves influence their technology adoption behaviors and continued usage over time (De Barba et al., 2016; Mun & Hwang, 2003; Tojib et al., 2022). For instance, Mun and Hwang (2003) found that goal orientation not only shapes the intention to adopt web-based technologies but also predicts their continued usage. A recent study by Tojib et al. (2022) examined how performance-focused goal orientations serve as motivational factors driving the adoption of service robots. In a similar vein, we argue that both types of performance goal orientation will have positive effects on a user's intention to continue using an AI chatbot, albeit for different routes.

Users high in PAP orientation are likely to see chatbots not merely as routine aids or ordinary productivity tools but as valuable assets that can explore novel solutions and expand their performance potential. Moreover, over time, PAP-oriented users often explore additional features of the AI chatbots that can further enhance performance. Thus, PAP-oriented users are likely to develop a strong intention to continue using the chatbot because they see it as a means to achieve and excel. The positive experience and the innovative advantages they perceive will reinforce their commitment to integrating the chatbot into their work tasks. Existing research on technology adoption in educational settings has shown that goal orientation significantly influences behavioral intention (Sharma & Srivastava, 2020). A recent study on the use of desktop virtual reality systems has confirmed that goal orientation affects learning behavior and outcomes (Luo & Du, 2022). The chatbots' intelligent capabilities align with their performance goals, offering opportunities for PAP-oriented individuals who actively seek high-performance pursuits (Cheng & Jiang, 2020). Hence, once PAP-oriented users find the chatbot beneficial for performance enhancement, they are likely to continue using it consistently.

On the other hand, users with PAV orientation tend to focus on preventing failure and avoiding negative evaluations (Elliot & Church, 1997). This motivation lies in minimizing mistakes or enhancing productivity. Within this mindset, AI chatbots are approached more conservatively—as tools for error prevention rather than exploration or innovation (Alhadabi & Karpinski, 2020). Such users are likely to use chatbots to verify information and ensure error-free task completion. This utilitarian approach aligns with a threat-avoidant coping strategy, in which the AI chatbot is primarily viewed as a preventive tool for usage (Cheng & Jiang, 2020). Research on goal orientation and technology adoption has confirmed PAV related to the preventive use of technology. If the chatbot helps them prevent mistakes and reduces their anxieties about task performance, they will be motivated to keep using it as a protective resource. PAV-oriented users might be initially hesitant adopters, but if they adopt the chatbot and it proves to be reliable, their fear of reverting to unsupported work will drive continuance. In other words, discontinuing use could reintroduce the risk of error, which they are keen to avoid. Therefore, we hypothesize:

H1a. PAP orientation is positively associated with continuance intention to use AI chatbots.
H1b. PAV orientation is positively associated with continuance intention to use AI chatbots.

Effect of PAP Goal on Hedonic Attitude and Novelty Value

PAP-oriented users are motivated to succeed, demonstrate competence, and gain recognition from others (Elliot & Church, 1997). Empirically, achievement-oriented users have been observed to report higher enjoyment when using interactive learning technologies because it feeds their sense of accomplishment and curiosity (De Barba et al., 2016). When using AI-powered chatbots, PAP-oriented users are likely to perceive them as innovative technologies that contribute to both achievement and personal growth. The stimulating nature of chatbots enhances users' sense of enjoyment, thereby fostering a positive hedonic attitude (Huang, 2015). This aligns with previous findings suggesting that individuals with a PAP orientation actively seek out experiences that reinforce their competence and support progress toward their goals.

In addition to valuing enjoyment, PAP-oriented users are likely to be drawn to novel and innovative tools that support their pursuit of excellence and distinguish them from others (Deci & Ryan, 1985). AI chatbots, with their advanced conversational capabilities and dynamic interactions, offer users novel ways to engage with technology and solve problems creatively. These unique and novel capabilities are particularly appealing to PAP users, who are motivated by the potential of such technologies to amplify performance and enhance recognition. As such, PAP orientation can positively influence the perceived novelty value of AI chatbots, leaving users to view them as innovative tools that provide a strategic advantage in achieving their goals (Gnewuch et al., 2017).

Prior research has demonstrated that the novelty and interactivity features of chatbots contribute to user satisfaction and continued engagement. For PAP-oriented users, this perception of novelty is not incidental but central to how they evaluate the usefulness and appeal of emerging technologies. By valuing both the experiential enjoyment and the performance-enhancing potential of chatbots, PAP individuals are more likely to develop favorable attitudes toward their use, which are anchored in both hedonic and novelty appraisals. Therefore, we hypothesize

H2a. PAP orientation is positively associated with perceived novelty value of AI chatbots.
H2b. PAP orientation is positively associated with hedonic attitude toward AI chatbots.

Hedonic Attitude, Novelty Value, and Chatbot Continuance Intention

Hedonic attitude refers to the joy and pleasure users experience when interacting with technology. Prior research, including the UTAUT framework, has highlighted hedonic motivation as a key predictor of technology adoption and continued usage (Dinh & Park, 2024; Venkatesh et al., 2012). Alalwan (2020) demonstrated that hedonic value has a positive influence on customers' continued intention to use mobile ordering apps. This is relevant for AI-powered chatbots, where the user experience goes beyond basic functionality to include engaging and enjoyable interactions that stimulate intrinsic motivation.

Chatbots offer users interactive and entertaining experiences that generate new ideas beyond mere functionality. By simulating human-like conversations and responding to a variety of inquiries, AI chatbots tap into users' desire for playful and stimulating interactions (Dinh & Park, 2024; Gnewuch et al., 2017). This sense of enjoyment fosters emotional engagement, encouraging users to continue using technology. Studies have shown that more enjoyable and engaging technologies are more likely to be used consistently over time (Akdim et al., 2022). As users become more familiar with the hedonic aspects of chatbot interaction, their intention to continue usage is reinforced. The emotional satisfaction derived from these experiences plays a central role in shaping continuance behavior.

Novelty value refers to users' perception of a technology's uniqueness and originality (Hirschman, 1980). Prior research highlights novelty as an important factor in shaping user perceptions of technological innovation and fostering post-adoption acceptance, particularly in the context of conversational agents and AI-powered chatbots (Ma & Huo, 2023). The novelty effect—the appeal associated with encountering a new and distinctive experience—significantly influences how users interact with emerging technologies. When users perceive technology as novel, they are more likely to experience heightened interest, curiosity, and enjoyment during use (Adapa et al., 2020). This enhanced engagement strengthens hedonic attitudes and reduces psychological resistance to adoption (Gatzioufa & Saprikis, 2022; Xie et al., 2022). In the case of AI chatbots, novelty plays an important role in capturing and maintaining user attention. Their human-like interactions, real-time responsiveness, and dynamic content delivery create an immersive experience, reinforcing continued usage.

As users become more familiar with novel features such as creative response generation and adaptive learning, they tend to develop more favorable perceptions of technology. This, in turn, increases their intention to continue engaging with AI chatbots over time. Novelty value not only enriches the overall user experience but also serves as a catalyst for exploring more advanced features. Hence, we hypothesize:

H3a. Novelty value is positively associated with continuance intention to use AI chatbots.
H3b. Hedonic attitude is positively associated with continuance intention to use AI chatbots.

Effect of PAV Orientation on Cognitive (Utilitarian) Attitude and Performance Expectancy

This instrumental evaluation of chatbots is likely to foster a positive utilitarian value or cognitive attitude, as PAV-oriented users perceive the technology as a reliable solution aligned with their goal of minimizing risk and ensuring task success (Senko & Harackiewicz, 2005). Thus, PAV users are likely to assess whether the chatbot helps them accomplish tasks without error. If it proves helpful in that regard, they tend to form a positive utilitarian cognitive attitude: the belief that the chatbot is an effective tool for preventive use. This corresponds to a rational approval of technology's value. In prior studies, technology anxiety has been mitigated when technology exhibits utility, leading to post-acceptance (Venkatesh & Bala, 2008). We expect a similar dynamic here: PAV leads to a focus on utility, which, if confirmed, yields a favorable cognitive evaluation.

Performance expectancy, a key concept in technology acceptance, refers to an individual's belief that technology has the potential to improve their performance outcomes (Venkatesh et al., 2003). This belief, closely tied to perceived usefulness, plays a crucial role in shaping attitudes toward continued use of technology. In this context, PAV-oriented users are also likely to form strong performance expectancy, which refers to the belief that using the technology will lead to error-free task execution (Venkatesh et al., 2003). Because PAV users focus on avoiding poor performance, once they trust the chatbot, they will strongly expect it to support task completion by catching errors and providing accurate information. Ma and Huo (2023) found that perceived performance expectancy contributed to users' cognitive and affective attitudes. By providing reliable support, AI chatbots meet users' expectations for task completion and instill greater confidence in utility. In line with this, Cheng and Jiang (2020) found that users with prevention-focused motives, which align with avoidance orientation, emphasized the accuracy and task support functions of AI tools. We, therefore, expect PAV-oriented users to place greater expectations on the chatbot’s performance benefits once they deem it reliable.

In summary, PAV individuals are more likely to form favorable evaluations of AI chatbots based on their utility and capacity to prevent failure. Their continued use is likely driven by a cognitive attitude of performance expectancy and utilitarian value. Therefore, we hypothesize:

H4a. PAV orientation is positively associated with utilitarian cognitive attitude toward AI chatbots.
H4b. PAV orientation is positively associated with performance expectancy of AI chatbots.

Utilitarian Cognitive Attitude, Performance Expectancy, and Chatbot Continuance Intention

Utilitarian cognitive attitude, also referred to as cognitive attitude, refers to an individual's beliefs about the utility and functional efficacy of focal technology (Fishbein & Ajzen, 1975). Cognitive attitude focuses on general beliefs and evaluations about technology artifacts. Such evaluative beliefs are well-documented to shape behavioral outcomes (Chong et al., 2022; Shao et al., 2024; Yang & Yoo, 2004) Extensive research on technology acceptance has demonstrated that cognitive attitude is a detrimental predictor of initial adoption and continued use (Davis, 1989; Tsaiyi et al., 2025; Venkatesh et al., 2003). More recently, Chong et al. (2022) confirmed through meta-analysis that cognitive attitude remains a critical predictor of sustained engagement with digital tools. Shao et al. (2024) found that cognitive beliefs significantly influence both the routine and extended use of AI-based voice assistants.

In the context of AI-powered chatbots, a utilitarian cognitive attitude explains how users form judgments about the system based on their own experiences and past interactions. This attitude is grounded in logical evaluation, focusing on whether the chatbot delivers useful and relevant information. When users perceive the chatbot as a practical resource, they are likely to continue using it. Such utilitarian attitudes represent an overall mindset toward technology, shaped by thoughtful consideration of its functional features and capabilities. Over time, repeated positive interactions strengthen these favorable perceptions, reinforcing the user's sustained use.

Performance expectancy is defined as “the degree to which an individual believes that using the system will help him or her attain gains in job performance” (Venkatesh et al., 2003, p.447), focusing on leveraging technology to enhance task efficiency. Prior research theorized that individuals’ performance expectancy reflects users’ beliefs that technology will improve efficiency and productivity (Jacob & Pattusamy, 2020; Upadhyay et al., 2022). In the context of chatbots, performance expectancy refers to the degree to which technology can effectively support task completion and improve outcomes by minimizing errors. This perception serves as a key driver of continuance behavior. For instance, Kuberkar and Singhal (2020) found that when users perceive chatbot recommendations as relevant and valuable, such as for public transportation, they are more likely to continue using the service. Similarly, several studies have validated performance expectancy as a core factor influencing sustained engagement with AI-powered tools (Camilleri, 2024; Chen et al., 2024; Chow et al., 2023). Performance expectancy centers on the perceived usefulness of the chatbot in achieving desired outcomes. For example, a user might think that using this chatbot will help them complete their task faster and more accurately. Thus, individuals motivated by performance enhancement are more likely to maintain their engagement with AI chatbots.

H5a. Utilitarian cognitive attitude is positively associated with continuance intention to use AI chatbots.
H5b. Performance expectancy is positively associated with continuance intention to use AI chatbots.

RESEARCH METHODOLOGY

Sample and Procedure

We tested the research model using a survey of experienced AI chatbot users. The target population consisted of working professionals who had used AI-powered chatbots for work-related tasks. We focused on a professional context because performance goal orientations are highly salient in work settings. Participant data were collected from individuals in the United States who had prior experience using AI chatbots, as facilitated by the Prolific platform. Platforms, including Prolific and Amazon's Mechanical Turk, are widely utilized by researchers to gather data from targeted respondents (Lam et al., 2025; Lim & Zhang, 2022). These online platforms are considered reliable and diverse compared to traditional student samples (Sheehan, 2018). A recent study showed that participants recruited through Prolific were more likely to pass attention checks and follow instructions accurately (Douglas et al., 2023).

Surveys were distributed via Qualtrics online platform. We included three filter questions at the beginning of the questionnaire and used attention filters to check whether respondents paid considerable attention while participating in an online survey (Kung et al., 2018).

A comprehensive set of survey instruments was developed, comprising two distinct sections. The first part features questions to explore various constructs outlined in our proposed model. To ensure the reliability of our survey, we carefully selected measurement instruments from established literature sources. Participants responded to these questions using a five-point Likert scale. The latter part of the survey gathered demographic information vital for our analysis, including gender, age, educational background, work experience, and years of experience with AI chatbots. To ensure the questionnaire items' clarity and consistency, we subjected them to multiple rounds of evaluation by three experienced researchers specializing in technology adoption research.

The study surveyed 295 participants, with a balanced gender distribution of 52% male and 48% female. As shown in Table 1, age distribution showed that most participants were between 26 to 35 years old (42%), followed by those aged 36 to 45 years (28%), 46 to 55 years (14%), and both the 18 to 25 and over 55 age groups each represented 8%.

Table 1. Summary of the Demographic Profile of Respondents

Characteristics	Value	Frequency (N = 295)	Percentage
Gender	Male	154	52%
	Female	141	48%
Age	18–25 years old	24	8%
	26–35 years old	124	42%
	36–45 years old	83	28%
	46–55 years old	41	14%
	Over 55 years old	24	8%
Education	High School	3	1%
	Bachelor's degree	186	63%
	Master's degree	94	32%
	Doctoral degree	12	4%

The survey data were analyzed using SmartPLS v4.1 in a two-phase process. First, we examined the measurement model's fitness and construct validity. Second, we evaluated the structural model to assess the strength and direction of the paths between the constructs.

Measures

This study used multi-item scales to capture users' perceptions of AI chatbots in a structured way. PAP goal orientation was evaluated using three items adapted from prior studies (Silver et al., 2006; Tojib et al., 2022) that reflect the use of chatbots as a source of inspiration and for generating new ideas. PAV goal orientation was measured with three items from Silver et al. (2006), which highlighted reliance on chatbots to identify potential errors and reduce task mistakes.

Novelty value was gauged through three items (Wells et al., 2010) assessing users' perceptions of chatbots as a novel experience. Hedonic attitude was assessed using three items (Rzepka et al., 2022; Venkatesh et al., 2003), capturing users' enjoyment and satisfaction derived from interacting with chatbots (Childers et al., 2001; Mun & Hwang, 2003). Performance expectancy was measured with three items (Menon & Shilpa, 2023; Rahi et al., 2019; Venkatesh et al., 2003) examining users' beliefs about chatbots' ability to enhance task efficiency and productivity. Utilitarian cognitive attitudes toward chatbots were evaluated with three items (Menon & Shilpa, 2023). Lastly, AI-chatbot continuance intention was measured to understand users' intentions to continue using chatbots in future tasks and work activities (Ashfaq et al., 2020). These measures collectively provide a comprehensive view of users' motivations, perceptions, and intentions related to ongoing engagement with AI chatbots.

DATA ANALYSIS AND RESULTS

Measurement Model Evaluation

After collecting the data, we assessed the reliability and validity of the constructs by employing three key metrics: Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE). According to Afzal et al. (2013) and Hair et al. (2021), Cronbach's alpha should exceed 0.70 to indicate acceptable internal consistency, while factor loadings should be greater than 0.50 to demonstrate adequate indicator reliability. For construct validity, CR values should be above 0.70, and AVE values should exceed 0.50.

Assessing Reliability, Validity, and Discriminant Validity

The measurement model indicated strong reliability and convergent validity for all constructs. As shown in Table 2, each construct's indicators had high factor loadings (all above 0.70), implying that the constructs explain a notable portion of the variance in their measures (Afzal et al., 2013).

Table 2. Construct Reliability and Validity

Construct	Item	Loadings	Cronbach's α (≥ 0.70)	Composite Reliability (≥ 0.70)	AVE (≥ 0.70)
Performance-Approach Goal Orientation (PAP)	PAP1	0.885	0.809	0.882	0.714
	PAP2	0.905			
	PAP3	0.873			
Performance-Avoidance Goal Orientation (PAV)	PAV1	0.715	0.844	0.904	0.759
	PAV2	0.865			
	PAV3	0.866			
	PAV4	0.814			
Novelty Value	NV1	0.761	0.764	0.864	0.680
	NV2	0.878			
	NV3	0.832			
Hedonic Attitude	HA1	0.920	0.913	0.945	0.852
	HA2	0.927			
	HA3	0.922			
Cognitive Attitude	CA1	0.779	0.704	0.818	0.601
	CA2	0.763			
	CA3	0.792			
Performance Expectancy	PE1	0.878	0.889	0.931	0.819
	PE2	0.909			
	PE3	0.928			

continued on following page

Table 2. Continued

Construct	Item	Loadings	Cronbach's α (≥ 0.70)	Composite Reliability (≥ 0.70)	AVE (≥ 0.70)
AI Chatbot Continuance	AIC1	0.822	0.771	0.868	0.686
	AIC2	0.781			
	AIC3	0.880			

Note. AVE = average variance extracted; AI = artificial intelligence.

Cronbach's alpha values exceeded the recommended 0.70 thresholds for internal consistency (ranging from the mid-0.80s to 0.90s), and CR scores were likewise well above 0.70 for every construct, indicating satisfactory to good reliability. Moreover, the AVE for each construct was well above the minimum criterion of 0.50, and all AVE values were ≥ 0.70, denoting that each construct captured over 70% of the variance in its indicators. These results confirm that all constructs met or exceeded the standard criteria for reliability and convergent validity (Cronbach's α > 0.70, CR > 0.70, AVE > 0.50), with no notable exceptions. The measurement properties are therefore sound, providing a solid foundation for examining structural relationships.

Assessing Discriminant Validity

Discriminant validity can be assessed by using the heterotrait–monotrait ratio (HTMT) analysis (Henseler et al., 2015). The HTMT criterion helps detect potential collinearity problems among the study's constructs (Hair et al., 2021). Discriminant validity issues arise when HTMT values are high. Henseler et al. (2015) suggested a threshold of 0.90 for structural models involving conceptually similar constructs. Table 3 reports the HTMT values between each pair of constructs, all of which fall below the conservative threshold of 0.85. In this study, the highest HTMT value observed was comfortably under 0.85, indicating that each construct is empirically distinct from the others. These results satisfy the HTMT criterion for discriminant validity, meaning that no construct overlapped excessively with any other regarding shared variance.

Table 3. Discriminant Validity–Heterotrait-Monotrait Values

Construct	PAP	PAV	NV	HA	UCA	PE	AICC
Performance-Approach Goal (PAP)							
Performance-Avoidance Goal (PAV)	0.445						
Novelty Value (NV)	0.421	0.382					
Hedonic Attitude (HA)	0.475	0.338	0.768				
Utilitarian Cognitive Attitude (UCA)	0.514	0.662	0.697	0.586			
Performance Expectancy (PE)	0.481	0.566	0.412	0.382	0.852		
AI Chatbot Continuance (AICC)	0.577	0.513	0.706	0.697	0.743	0.689	

In addition, the traditional Fornell–Larcker criterion was met (Fornell & Larcker, 1981; Henseler et al., 2015). Table 2 shows that each construct's AVE exceeded the squared correlations with other constructs, further reinforcing that the constructs in the model are well differentiated. Overall, the measurement model in both Tables 2 and 3 shows good discriminant validity, as evidenced by the HTMT ratios and AVE, ensuring that the structural path estimates are free from multicollinearity issues.

Results

Table 3 reports path coefficients and p-values from the hypothesis tests. The structural model evaluating H1a–H5b is summarized in Table 4. Overall, the model explains a substantial portion of the variance in the endogenous constructs, and most hypotheses are supported.

Table 4. Questionnaire Content, Variables for Each Construct

Construct	Measurement Items
Performance-Approach Goal Orientation (PAP)	I use AI chatbots as source of inspiration to generate ideas.
	I have used AI chatbots to generate new ideas for my tasks.
	Using AI chatbots helped me come up with new ideas for my work tasks.
Performance-Avoidance Goal Orientation (PAV)	I primarily like to use AI chatbots to identify errors for my task.
	When using AI chatbots, my focus is on utilizing it to reduce errors within my tasks.
	Using AI chatbots helped me fix errors in my tasks. AI chatbots helps me stay focused on avoiding mistakes in my tasks.
Novelty Value	I found using AI chatbots to be a novel experience.
	Using AI chatbots is new and refreshing.
	AI chatbots made me feel like I was exploring a new world.
Hedonic Attitude	I have fun interacting with AI chatbots.
	Interacting with AI chatbots is fun.
	Interaction with AI chatbots is enjoyable.
Utilitarian Cognitive Attitude	Using AI chatbots is effective.
	Using AI chatbots is helpful.
	AI chatbots is practical.
Performance expectancy (PE)	Using AI chatbots helps me accomplish things more quickly.
	Using AI chatbots would improve my task productivity.
	AI chatbots enables me to complete the task efficiently.
AI Chatbot Continuance	I intend to continue using AI chatbots in the future.
	I think using AI chatbots will increase my future tasks.
	I plan to continue using AI chatbots in my work.

Note. AI = artificial intelligence.

Table 5 summarizes the hypotheses' results.

Table 5. Path Coefficients and the Results of the Significance Tests

Hypothesis	Path	Coefficient	P values	Confirmed
H1a	Performance-Approach Goal → AI Chat Continuance	0.145	0.008	Yes
H1b	Performance-Avoidance Goal → AI Chat Continuance	0.008	0.865	No
H2a	Performance-Approach Goal → Novelty Value	0.404	0.000	Yes
H2b	Performance-Approach Goal → Hedonic Attitude	0.456	0.000	Yes
H3a	Novelty Value →AI Chat Continuance	0.143	0.030	Yes
H3b	Hedonic Attitude →AI Chat Continuance	0.258	0.001	Yes
H4a	Performance-Avoidance Goal → Utilitarian Cognitive Attitude	0.545	0.000	Yes
H4b	Performance-Avoidance Goal → Performance Expectancy	0.593	0.000	Yes
H5a	Utilitarian Cognitive Attitude → AI Chatbot Continuance	0.190	0.027	Yes
H5a	Performance Expectancy → AI Chatbot Continuance	0.244	0.008	Yes

Note. *p < 0.05; **p < 0.01; ***p < 0.001; AI = artificial intelligence.

Hypotheses H1a and H1b tested the direct influence of performance goal orientations on chatbot continuance. H1a posited that PAP orientation positively influences continuance. H1a was supported: PAP orientation showed a positive and statistically significant direct effect on continuance intention ($\beta = 0.145$, $p = 0.008$, supporting H1a). In practical terms, users with higher PAP are more likely to intend to continue using the chatbot. By contrast, H1b predicted that PAV orientation would affect continuance. The results did not support H1b; the path from PAV orientation to continuance was essentially zero and non-significant ($\beta = 0.008$, $p = 0.865$).

Hypotheses H2a and H2b examined whether a PAP orientation would foster greater perceptions of novelty and enjoyment. The data provides strong support for both relationships. PAP had a significant positive effect on perceived novelty value ($\beta = 0.404$, $p < 0.001$) and users' hedonic attitude ($\beta = 0.456$, $p < 0.001$). In turn, novelty value and hedonic attitude had positive influences on continuance ($\beta = 0.143$, $p = 0.030$ and $\beta = 0.258$, $p = 0.001$, respectively), supporting H3a and H3b.

Moreover, both novelty value and hedonic attitude were found to predict continuance intention, thereby supporting H3a and H3b significantly. Novelty value positively influenced continuance ($\beta = 0.143$, $p = 0.030$), confirming its role as a partial mediator between PAP orientation and sustained usage. Likewise, hedonic attitude significantly influenced continuance intention ($\beta = 0.258$, $p = 0.001$), highlighting the role of emotional gratification in user engagement.

Hypotheses H4a and H4b focused on PAV orientation's influence on cognitive attitude and performance expectancy. Both were supported ($\beta = 0.545$, $p < 0.001$; $\beta = 0.593$, $p < 0.001$). These in turn significantly predicted AI chatbot continuance (H5a: $\beta = 0.190$, $p = 0.027$; H5b: $\beta = 0.244$, $p = 0.008$).

Additionally, both utilitarian cognitive attitude and performance expectancy were significant predictors of continuance intention, providing support for H5a and H5b. This finding suggests that users who form favorable beliefs of chatbots' utility are more likely to continue using them. Similarly, performance expectancy positively influenced continuance intention ($\beta = 0.244$, $p = 0.008$). This highlights the importance of demonstrating concrete utility, such as improved efficiency, to promote long-term engagement. Overall, the results reinforce the importance of both rational evaluations and outcome expectations in driving sustained use.

DISCUSSION

This study demonstrates that performance goal orientations—PAP orientation and PAV orientation—systematically influence post-adoption evaluations and continuance intentions toward workplace AI chatbots. We proposed a dual-pathway model: PAP orientation is associated with a higher perceived novelty value and stronger hedonic attitudes, whereas PAV orientation is associated with higher performance expectancy and stronger utilitarian cognitive attitudes; both pathways support continuance. Empirically, our research revealed a complex relationship between PAP orientation and continuance that is both direct and indirect, operating through novelty and hedonic evaluation. Similarly, the influence of PAV orientation is primarily indirect, working through utilitarian evaluation and performance expectancy, with only a weak direct association after accounting for these mediators. These patterns help reconcile prior mixed findings on continuance by highlighting motivation-driven heterogeneity in evaluative pathways. Sustained engagement depends not only on the qualities of the system but also on the motivational dispositions that users bring to their interactions.

Theoretical Implications

This study contributes to the theoretical understanding of technology post-adoption behavior by introducing performance-goal orientation as a significant antecedent of chatbot continuance. To the best of our knowledge, it is among the first empirical investigations to integrate goal-orientation theory with IS continuance models in the context of AI chatbots. The findings show that users' motivational orientations systematically shape their evaluative perceptions of AI chatbots, which in turn affects sustained use. Our results add a motivational-psychology dimension to existing continuance frameworks, which have traditionally emphasized cognitive beliefs and affect while treating user traits as exogenous.

One key theoretical implication is the differentiated role of hedonic versus utilitarian evaluative values in driving continuance among different user segments. Prior continuance models generally include both enjoyment and perceived usefulness as predictors, implicitly assuming that these factors additively influence all users' behavioral intentions. Our results indicate that PAP users tend to exhibit higher hedonic attitudes and novelty perceptions, which strongly drive their continuance. In contrast, PAV users rely more on utilitarian attitudes and performance expectancy to sustain their continuance. In other words, there are distinct continuance pathways: an intrinsically motivated pathway that is more active among PAP users, and an extrinsically motivated pathway that is more active among PAV users. This finding suggests that the relative weight of hedonic versus utilitarian factors varies across users and highlights the importance of considering user segments in models of postadoption behavior.

Moreover, by drawing on goal orientation theory, this study connects IS research with a rich stream of motivational psychology. The distinction between PAP and PAV orientations is meaningful for explaining technology-sustained usage behaviors, whereas earlier research often considered motivation in a unidimensional way. Our findings show that not all motivation is the same—the desire to excel versus the desire to avoid failure can lead to different usage patterns and evaluations. This insight broadens theoretical perspectives in IS by offering a more nuanced view of user motivation and echoes calls for more integrative models that incorporate personality or dispositional factors in technology postadoption.

The positive relationship between hedonic attitude and AI chatbot continuance highlights the importance of enjoyment in sustained use. For PAP individuals, this finding aligns with their motivation for hedonic value, supporting the idea that engaging technologies are more likely to be used continuously. Therefore, designing AI chatbots that satisfy the novelty and hedonic needs of performance-oriented individuals is crucial for fostering long-term engagement. Conversely, PAV goals show no significant direct effect on AI-chatbot continuance but do influence utilitarian cognitive attitude and performance expectancy, indicating a preventive orientation that prioritizes practical benefits and error avoidance. This is evidenced by the strong path coefficients between PAV goals and utilitarian value as well as performance expectancy, suggesting that individuals with a PAV orientation are primarily concerned with understanding and predicting chatbot performance to prevent errors during use. These users show a clear preference for tools that minimize errors and ensure reliability, thereby emphasizing practical, error-averse benefits.

Practical Implications

The findings of this study offer several practical implications for future practice. First, the results provide guidance for designing chatbots that align system features with users' motivational orientations. To encourage adoption and continued use, organizations should emphasize novelty and enjoyment for PAP users, who are motivated by innovation and hedonic value. Features such as creative solutions, gamification, and engaging interactions can strengthen long-term engagement.

Second, organizations can segment their user base according to motivational orientation. By personalizing the chatbot experience for each segment, they can better address users' specific needs. For PAP users, who thrive on achievement and novelty, the interface can highlight creative and challenging functions. In contrast, for PAV users, the focus should be on features that help identify issues and prevent errors. PAP users may perceive the chatbot as an exciting partner in innovation, whereas PAV users may see it as a task-oriented assistant that emphasizes preventive measures.

Third, PAV orientation shows no significant direct effect on continuance intention; its impact is indirect, mainly through utilitarian evaluation and performance expectancy. Training and onboarding should reflect this by providing users with accuracy-focused workflows, performance safeguards, and reliability assurances.

Limitations and Future Research

Although this research follows standard research guidelines, it is important to acknowledge its limitations. First, the current research focuses on goal orientation and performance-related factors in chatbot continuance but does not consider other potentially important contextual elements, such as task complexity.

Complexity can reflect variability in inputs, interdependence with other systems or people, time pressure, exception handling, and the cost of errors. Future work should measure these facets explicitly and test whether complexity moderates the links between PAP and PAV orientations and hedonic versus utilitarian evaluations. Experimental manipulations involving routine versus non-routine tasks and low-stake versus high-stake scenarios, along with field studies that link task attributes to usage logs, would clarify when each pathway is most influential.

Second, the evidence is based on a single-country sample, which limits external validity. Cross-national and multi-industry designs can assess whether motivational orientations and attitudes toward AI chatbots vary with cultural norms, demographics, or regulatory contexts. Multilevel models, with individuals nested within organizations and countries, would separate within- and between-context effects and show whether the relative weights of novelty and hedonic value versus performance expectancy shift across settings.

Third, the cross-sectional design offers only a snapshot of a situation. In contrast, longitudinal approaches allow researchers to track how orientations, evaluative beliefs, and intentions continue to evolve over time. To analyze these changes, researchers can employ cross-lagged panel models to assess the timing and durability of the effects. Furthermore, implementing randomized interventions can enhance the validity of causal conclusions.

A further limitation is the presence of individual differences beyond goal orientation. The Big Five traits—openness, conscientiousness, extraversion, agreeableness, and neuroticism—might influence evaluative pathways and continuance: openness reinforces the novelty and hedonic route; conscientiousness promotes sensitivity to reliability and performance expectancy; extraversion augments responsiveness to socially rich features; agreeableness maintains trust and willingness to follow guidance; neuroticism elevates risk aversion. Integrating validated Big Five measures, testing personality-moderated mediation, and examining possible curvilinear effects would explain heterogeneity in engagement and allow more precise personalization, offering practical implications for psychology.

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CORRESPONDING AUTHOR

Correspondence should be addressed to Chang Heon Lee: changheon@csufresno.edu

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Chang Heon Lee is an associate professor of information systems and decision sciences at the Craig School of Business, California State University, Fresno. He earned his Ph.D. in Management from the Eller College of Management at the University of Arizona, his M.S. in Management Information Systems from Indiana University Bloomington, and his B.S. in Electrical Engineering from Korea University. His research focuses on FinTech, business intelligence, and healthcare analytics, and has been published in journals including the Journal of the Association for Information Science and Technology, Communications of the Association for Information Systems, Internet Research, Industrial Management & Data Systems, and Sustainable Computing: Informatics and Systems, as well as in various conference proceedings, including the Hawaii International Conference on System Sciences.

Stephen Choi is an Associate Professor and Craig research fellow at the Information Systems and Decision Sciences Department, Craig School of Business, California State University (CSU) Fresno. He received his B.S. & M.S. in MIS, and Ph.D. in Information Systems from New Jersey Institute of Technology and B.A. & M.S. in Chemistry from Rutgers University. He worked ten years professionally as Chemist and Computer Systems Validation Manager at Pfizer Pharmaceuticals Research Labs in New Jersey. With the current position at CSU Fresno, he is serving as the Artificial Intelligence Program Coordinator where he developed two key AI courses – Machine Learning Applications & Emerging Topics in AI, and overseeing the program. He is active in the research areas of artificial intelligence, machine learning, social and mobile computing, and HCI. His recent publications appeared in Information & Management, International Journal of Electronic Commerce, Computers in Human Behavior, Journal of Information & Software Technology, IEEE Transactions of Professional Communication, International Conference of Information Systems (ICIS), Americas Conference of Information Systems (AMCIS), Hawaii International Conference of Systems Sciences (HICSS), and more.

Dr. Ojoung Kwon is a Professor of Computer Information Systems in the Craig School of Business at California State University, Fresno. Dr. Kwon holds a BS and MS in Electronics Engineering and an MBA with an MIS specialization. He received a Ph.D. in Management Science and Artificial Intelligence from the University of Alabama in 1991. Before teaching at the Craig School of Business, Dr. Kwon was an associate professor at the University of Illinois at Springfield. He taught for 11 years and developed and delivered five fully online graduate MIS courses (Database, Expert Systems, Decision Support Systems, Neural Networks, and Project Management) via UI-Online. Dr. Kwon's teaching/research interests are database management systems, data warehousing and mining, Artificial Intelligence and Machine Learning, and Cybersecurity. Dr. Kwon has conducted various high-caliber research projects with many organizations, including AT&T, General Motors, Alabama Power Company, Amdahl Communications, Illinois Division of Oral Health, US Department of Transportation, Administrative Office of Illinois Courts, and Strategic Missile Commander. He has numerous publications and presentations; received many grants, fellowships, and awards; and has been listed in the Who's Who in the World, Who's Who in America, and Who's Who in Science and Technology. He also served on many committees and boards in private, public, and academic organizations.